Two general classes in creative problem-solving? An account based on the cognitive processess involved in the problem structure-representation structure relationship.

Ana-Maria Olteţeanu [1]

Abstract. The creative problem-solving performed by natural cognitive systems includes a wide variety of tasks of different degrees of difficulty. A classification of creative problems in two broad categories is proposed, based on problem structuredness and the cognitive processes used in regulating the problem structure-representation structure relationship in creative problem-solving. A cognitive theoretical framework is used to exemplify the difference in cognitive processes participation in these two classes of creative problem-solving.

1 Introduction

Riddles, remote associate tests [20], creative affordance tasks[2], to insight problem-solving and creative discovery are all considered creative problem solving tasks. Despite sharing this vague abstract categorization, these tasks vary widely in difficulty, involving from a cognitive standpoint a variety of mechanisms and different types of sensory information. For the cognitive modeler, the task of modeling creative architectures thus becomes extremely complex, with processes implicating most elements of any cognitive architecture.

Moreover, to respond to Newell's call for unification [25], creative cognitive architectures need to be able to solve (or at least prove they have extensible abilities for the future modeling of) all such types of problems.

This issue is not yet solved in the field of computational creativity [17, 27, 6] either. However, creative problem-solving, though more constrained in its evaluation than the field of general creativity (as problems have to be solved), could benefit by using a process-based distinction in its classification, akin to Boden's [5] differentiation between combinatorial and exploratory-transformational creativity.

A more rigorous treatment of the main processes involved in creative problem-solving and the classification of such problems is necessary, in order to prepare the ground for further computational modeling of creative problem-solving tasks and the implementation of artificial creative cognitive systems. This classification should be relevant for both natural (humans, some animals [13, 1]) and artificial cognitive systems.

This paper approaches such a classification from the perspective of degree of problem structure, the representation structure needed to problem solve and cognitive processes involved in accessing the information necessary to create such a representation structure.

The rest of this paper proceeds as follows. Initial coarse levels of creative problem-solving are differentiated in Section 2, by comparing such problems to well-structured problems. The classification is based on the type of processes used to compensate at the representation level for the lack of structure in the problem. A set of common principles for creative problem-solving (no matter the process) is proposed in Section 3. A three-level theoretical framework for creative cognitive architectures [26] proposed to address a large variety of creative problems is presented in more formal detail in Section 4, in order to build the analytical apparatus of process-based distinctions. This is used in Section 5 to illustrate two problem classes based on (two) distinct processes of creative problem solving. Finally, the general implications of such a distinction are discussed in Section 6, followed by conclusions and further work in Section 7.

2 Problem structure and coarse levels of creative problem-solving

In contrast to the well-structured spectrum of problems encountered in classical problem solving [23], insight problem-solving and creative discovery deal with ill-structured problems [24], the solving of which is posited to be related to implicit processing [31, 4, 11]. Such problems don't seem to proceed in incremental, step-wise fashion, with problem-solvers unable to predict their level of progress or closeness to the solution [21]. The elements of the initial problem state might not be crisply defined - as practical and abstract problem elements (concepts) from different fields can be brought to bear in creative problem-solving. With the initial state not necessarily closed, or the objects and relations set of this state not made salient, successor functions are not clear nor salient either. Such problems present initial saliency towards wrong or unsatisfactory kinds of representation, with re-representation being the process which transforms an ill-structured problem in a well-structured one with direct inference to a problem solution.[3]

However, well-structured problems are rarer and more artificial than initially thought, with some [30] positing a continuum of degrees of problem structuredness.

In the following we differentiate coarsely between a few levels of creative problem solving. This differentiation is based on a com-

[1] SFB/TR 8 Spatial Cognition, Universität Bremen, Enrique-Schmidt-Str. 5, 28359 Bremen, Germany, email: amoodu@informatik.uni-bremen.de

[2] Finding a replacement object to perform a certain task when the main tool is missing (i.e. put a nail in the wall in the absence of a hammer).

[3] In some ways easier than most well-structured problems, as the inferences seem to proceed directly once the representation has been found.

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parison between the amount of structure in such problems and well-structured problems:

- Normal well-structured problems can become **creative problems** when one of the elements required to apply a certain heuristic to the problem is not present; thus a new element needs to be found creatively which can act as an (often imperfect) replacement.
- **Insight problems** - The structure required for the solution might be present in the memory of the cognitive system, but is not salient from the problem proposal; various elements of the problem or problem representations structures might need to be brougth forward from the memory, or the environement, yielding new possible succesor functions; once such objects are clear, the succesor function is found and the goal is achieved with ease.
- **Creative discovery problems**[4] - The structure required for the solution is not present in the memory of the cognitive system, but needs to be created - though some of the elements are clear. This involves more than a representational shift to the less-salient, better suited representation structures; it requires the production of an accomodating problem structure representation.

These levels are however intertwined. A simple example of creative problem-solving is the case of creative affordance problems. When needing an object with a particular affordance for a task or routine, given that the object is missing, the human can find or improvise a replacement out of an object which can give the same affordance - e.g. when lacking a cup to store, transport water and drink from, a human can use a variety of other containers. However, this type of creative search for an object happens in a variety of insight problems as well. In the string problem [18], in order to make one of the strings a pendulum, the participants need to use one of the objects in the room as a weight. Applying a pendulum concept to solve the problem is the insight level of creativity here, while finding a way to make a pendulum out of a string and pliers is simpler, involving a "lower" level of creativity.

We propose that the lack of (appropriate) structure at various levels within such problems influences the cognitive processes of the solver, which need to compensate by finding a way towards a productive structure. The different ways in which a cognitive systems seeks such structure compensation constitute process differences which can be used for a cognitive classification of such problems.

3 Principles of creative and insightful problem-solving

The following common principles are proposed to be part of the processes of both insightful and creative problem-solving. Principles 1-6 are general, while principles 7 and 8 are specific to the framework described in Section 4.

1. To start solving any problem requires a stage of problem interpretation. Interpreting a problem means building a problem representation. This interpretation step is sometimes ignored in classical AI problem-solving accounts, or considered a trivial transition from the represented world to the problem representation itself, as the problem is structured enough, making the representation of its structure trivial.
2. The problems representation includes/eludes and emphasizes various elements of the given set of objects in the problem and various relationships between them. These constitute the representation structure RS that the agent assigns to the problem.

[4] This description does not refer to nor include serendipity.

3. The chosen RS is essential, as further inferences that can be made are determined by it. The RS of ill-structured problems is disputable and changeable. Various RS's might lead to various inferences and ways of attempting to solve the problem.
4. Creative problem-solving is a process of searching for or constructing a representation which brings about a valid and productive initial problem state hypothesis.
5. Salient structures (or relationships, structure-affordance pairs) can detract the solver, by getting him stuck in functional fixedness.
6. The (meta-search or creative) solving ends when a representation is found or constructed which seems to give the solver the opportunity to make direct fruitful inferences leading to a solution. Such representations or hypotheses are tested. Then the process restarts taking into account the new information generated via testing as needed.
7. Each RS is composed of various connected elements: concepts, problem templates known to the solver (all these can be thought of as structures themselves), their relationships and information about their features and uses.
8. This search or construction of a productive RS can be performed using a) the concepts involved, the problem structures they yield, the features they contain (structural information) and b) the similarity neighborhood of the concepts involved, of their features, of the problem structures they have been involved in (semantic information) together with knowledge about their affordances (functional information). (These have been discussed in [26] and will be described in more formal detail further.)

4 A three-level framework for creative processing with representation structure

The need for representation structures is acknowledged in cognitive science and artificial intelligence by the invention and sometime interchangeable use of a variety of concepts: image schemas, templates, cognitive maps, frames and schematas [22], scripts [29], mental models, etc. The importance of structure, structural transfer and abstraction from initial structure in cognitive processes is further acknowledged in analogy [10], metaphor [15, 16] and developmental accounts of concept generation [19].

In the previous section, problem structure (and lack thereof) has been related to creative problem-solving. Thus, the less structure there is in the initial problem state, the more the cognitive system needs to rely on internal abilities to provide a working representation structure. If searching for or creating such a representation structure out of information already held in the solver's knowledge base (KB) is the main issue in creative problem-solving, then any framework or cognitive architecture which aims at implementing creative problem-solving must posit memory (or knowledge representation) structures and processes which support such search and generative processes. The following hybrid three-level theoretical framework previously proposed in [26] aims to do just that. In the following, the three main components of the framework are presented (subsymbolical spaces 4.1, concepts 4.2 and problem templates 4.4), together with the processes they support (hypothesizing by concept similarity 4.3, creative use of problem template 4.5).

4.1 Subsymbolical spaces/Sensorimotor maps

Subsymbolical feature spaces organized by similarity metrics constitute the bottom level of this framework. Such feature spaces are to be understood as sensorimotor. This level can contain a feature space

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classifying the colors perceived by the cognitive system, a shape space which organizes memorized reproduceable shape patterns by similarity, a space which organizes motion trajectories, be it external or proprioceptive etc. To maintain generality, a limited set is not explored or proposed here, as it would be implementation-dependent. The similarity metrics correspond to the feature space itself and the type of sensor which is doing the encoding. Higher similarity is assumed to correspond in the encoding to neighborhood closeness, or other form of faster access (i.e. a stronger connection between the two features).

However, any concept is to be understood the activation of a particular point in a collection of feature spaces. This type of anchoring is meant to allow memory search in the similarity neighborhood spaces of the various component features of each concept[5].

Conceptual discovery and transformation are general problems of creative cognition. However, any conceptual representation that wants to be in line with cognitive research needs to deal in one way or another with the issue of grounding concepts. Various stances on the grounding of mental representation exist, e.g. functional role semantics, informational semantics, structural isomorphism, grounding via perception and action [2, 3], etc. This framework acknowledges the need for grounding. In what follows, concepts are going to be treated as symbolic entities, anchored in such subsymbolic feature spaces.

4.2 Concepts

Let C be a set of known concepts, $C \in KB$, where KB is a cognitive system's knowledge base, with

$$c_1, c_2, c_3, ..., c_m \in C$$

Via perceptual experience, agent α has acquired in its KB sensory, motor and semantic knowledge maps, which are organized via a similarity metric specific to the map. Knowledge about each concept is an activation of features known to belong to the concept, distributed over these maps. Thus we define A a set of known affordances (motor actions), V a set of known visuospatial features, S a set of known semantic tags,

$$\{a_1, a_2, a_3, ..., a_n\} \in A$$
$$\{v_1, v_2, v_3, ..., v_o\} \in V$$
$$\{s_1, s_2, s_3, ..., s_p\} \in S$$

so that:

$$C \subset P(A) \times P(V) \times P(S)$$
$$C = (A', V', S'), A' \subset A$$

There is no need for a concept to manifest activation along all these maps, it can very well be that:

$$\exists c_x \in C, \quad c_x = (A', V', S') = \{\emptyset, v_i, v_j, s_i\}$$
$$\exists c_y \in C, \quad c_y = (A', V', S') = \{a_i, v_k, \emptyset\}$$

Knowledge can be added to all sets C, A, V, thus when a $c_z \notin C$ is observed, it is added to the set, together with the corresponding observed affordances in A, visuospatial features in V, semantic tags in S, where the insertion point in these maps is based on similarity metrics specific to such a map.

Activation over new features can be added as part of a concepts in KB, if known concepts with new features are observed:

Known: $c_3 = \{green, round, to\ eat, apple\}$

Observed: $c_3 = \{yellow, round, apple\}$

Then in KB: $c_3 = \{green, yellow, round, to\ eat, apple\}$

New semantic tags (object names) can be added in the same manner:

Known: $c_3 = \{green, red, round, to\ eat, apple\}$

Observed: $c_3 = \{green, round, pomme\}$

New: $c_3 = \{green, red, round, to\ eat, apple, pomme\}$

Inferences about objects in the environment can be drawn on their names or a subset of features, by activating a known concept. Thus receiving from the environment the subset:

$$s_1 = \{round, to\ eat\}$$

can trigger

$$c_{24} = \{green, red, round, to\ eat, apple\},$$
$$c_{26} = \{orange, round, to\ eat, orange\},$$
$$c_{28} = \{yellow, round, to\ eat, pomelo\}$$

in various orders, depending on the respective concepts'activation function in the specific KB (this accounts for individual experience with various objects). [6]

The encoding system can allow for the formation of complex and abstract concepts by enlarging its element set to involve other concepts and a relation set R. Thus:

- the concept with the semantic tag s_{10} *apple* is an activation of a visual color point or subgroup v_1 on visual color space, an activation v_2 over a shape map, and an activation a_5 of affordances.
- the concept with the semantic tag *apple garden* is a composed concept which draws on both concepts *apple tree* and *garden*, specific relationships between them (e.g. r_9 - *apple trees* part of the *garden*) and affordances connected to some such relationships (*apples* grow on *apple trees*, *apple trees* grow in the *garden*).
- concepts which represent composed objects (e.g. *fishing rod*) can be represented as an activation of the various composing parts (*rod*, *fishing line*, *hook*, etc.), their relations (e.g. attached to, elongates) and affordances (e.g. fishing).
- abstract concepts like *Justice* can be understood as an activation over a set of concepts like *integrity*, *rights*, *property*, *balance*, *wellbeing*, emotional areas (sets of reactions) to various actions involving the previous concepts, consequence chains, etc.

Some of these complex or abstract objects lend themselves better to encoding via RS's akin to problem templates (see Section 4.4).

Comprehension of the system is a collection of activations of the concepts in its KB corresponding to the objects present in the scene

[5] Such search can be envisaged on more than feature-similar spaces - e.g. context similarity might play a role in faster access between two items, and therefore in the organization of such maps. In this framework, search via context similarity is mediated by higher level representation structures (the context).

[6] This could of course be done by propositional means; however, when more specific features in appropriate feature spaces are used (i.e. encoding of shape contour, which is hard to describe by propositional means), the item can be ellicited out of the KB with more accuracy, and comparison can be performed with feature-specific tools.

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that the system is observing. Thus every scene SC is comprehended as a collection of concepts - $SC = \{c_1, c_3, c_7\}$ - their known or observed features, relations and affordances, where some affordances, concepts or objects, and relations might not be known. Unknown objects can be understood via analogy and/or learned (added to the knowledge base) in a preferential fashion, when either:

- they are something the agent is focusing on (thus deploying attention/activation resources to);
- they are connected to a concept the agent already knows (thus the concept already holds activation power as a unit);
- they are similar to something known;
- they are entirely new;

depending on whether the agent is in an exploratory/inquisitive mode, in an analytic or creative problem-solving mode (or on the nature of the individual agent). Each strategy comes with its own type of gains and trade-offs.

A higher degree of attention payed to a certain set of objects adds a higher degree of activation to the concept in the system's memory, however the activation of the previous concepts that the system has seen might still be present (dropping over time), as to provide noise in the system, account for cognitive bias effects and generally provide new overlaps and relations. In this context, short-term memory is defined as the number of items which can be active at the same time, considering that some such items may be representation structures which contain multiple elements (akin to chunks).

Activation of particular concepts can trigger activation of specific higher-level (multiple-element) representation structures in the KB of the agent (see 4.4). In the case of problem-solving, such representation structures may be problem templates which include the objects in the scene. If such problem templates are activated though they do not constitute productive representation structures for the problem at hand, the agent can get stuck in functional fixedness.

4.3 Hypothesizing by concept similarity

Because of the distributed encoding, concept similarity can be computed between concepts by comparing their elements. Thus, because of their common affordance and visual feature elements, $c_1 = \{a_1, a_2, v_1, v_2, s_1\}$ and $c_2 = \{a_2, a_3, v_1, v_3, s_2\}$ can be considered similar.

Further, remember that A, V and S are spaces over which the similarity metric is meaningful and representative of the respective space, as proposed in [26]. Thus similarity ratings can be obtained within A, V and S between different elements.

Both these types of similarity ratings can be used for hypothesizing. Due to space concerns, in the following we will show a few examples of the element-based similarity hypothesizing.

Consider an agent that knows:

$$c_1 = \{a_1, a_2, v_1, v_2, s_1\}$$

$$c_2 = \{a_2, a_3, v_1, v_3, s_2\}$$

Then c_1 and c_2 overlap in a_2 and v_1.

$$c_1 \cap c_2 = \{a_2, v_1\}$$

If both c_1 and c_2 are associative synaptic bindings, the activation $f_C(c)$ traveling across both associative synaptic paths of c_1 and c_2 will strengthen the connection between their overlapping features:

$$f_C(a_2, v_1) = f_C(c_1) + f_C(c_2)$$

Now consider a c_3, the affordances of which are unknown:

$$c_3 = \{v_2, v_3, s_3, a_?\}$$

The system will check its similarity with known concepts, select c_1 and c_2 as most similar, and notice some degree of feature overlap:

$$c_3 \cap c_1 = \{v_2\}$$

$$c_3 \cap c_2 = \{v_3\}$$

The system will then propose that some of the affordances which hold for c_1 and c_2 might hold for c_3. A direct correlate relation between such visuospatial features and an affordance does not exist:

The query: $?\exists a_x \in A, f_C(a_x, v_2, v_3) \geq 0$ returns false.

The system could propose as a general hypothesis that c_3 inherits the affordances of the concepts it overlaps:

$$c_3 = \{?a_1, ?a_2, ?a_3, v_2, v_3, s_3\}$$

However, because of the previously observed strong correlation $f_C(a_2, v_1)$ and $v_1 \notin c_3$, the hypothesis can be refined one step further, with only a_1 and a_3 being proposed as possible affordances to check for in the real world for c_3.

4.4 Problem templates

The need for structured representation has been previously mentioned. Such structured representations can be acquired in a variety of ways. Some concepts or sets of objects can be bound together because of being encountered in a similar context (e.g. knives, forks and plates). Other such structured representations are dynamic, binding concepts to the actions that involve them (e.g. a juggler throwing balls in the air in a certain motion pattern is such a representation). In some such structured representation, the element of episodic arrangement (the order of actions) plays an important role (ex. Tower of Hanoi problems presuppose a certain kind of movements on the part of the solver, with some motion order strategies leading to success).

Such forms of representations bind together concepts, relations, action (or motion) sequences in higher order templates. Problems which have been solved can be encoded together with their solution, in a form which allows the further use of their structure.

Thus each problem template PT is a collection of concepts in C, relations between concepts in R, heuristics (understood as a productive set of known moves) in H, and solution state tags in SOL:

$$PT \subset P(C) \times P(R) \times P(H) \times P(SOL)$$

$$PT = (C', R', H', SOL'), C' \in C, R' \in R, H' \in H, SOL' \in SOL$$

Example: $PT_1 = \{c_1, c_2, c_3, r_1(c_1, c_2), h_1(c_1, c_2, c_3), sol_3\}$

The solution state tags can be used in the search for an appropriate PT when the desired result is known. Heuristics can also be triggered when a subset of concepts or objects is present in the environment or problem presentation, or when a relation or a composing heuristic within the problem presentation is made salient. Agents can be assumed to have preferential heuristics due to familiarity, expertise, bias, represented in KB as strong associations. Heuristics can be built compositionally as a set of moves between objects participating in the template:

$$h_1 = h_2(h_3(c_1, c_2), h_3(c_2, c_3))$$

The number of objects participating in a heuristic or some of their affordances can be constrained by the problem template, however they are cases where the slots can be understood as placeholders and are not bound to specific objects.

Cooking a recipe like h_{15} = *Pasta bolognese* is a collection of actions *mix, stir, chop, season, simmer* over the concept ingredients $C = \{c_1\ minced\ meat, c_2\ onion, c_3\ tomatoes, c_4\ mushrooms, c_5\ pepper, c_6\ basil, c_7\ oregano, c_8\ pasta\}$.

The collection of actions required is $\{h_1\ \ stir, h_2\ \ chop, h_3\ \ season, h_4\ \ simmer, h_5\ \ fry\}$, where each of these is a primitive cooking template. For example $h_1\ stir = \{foods\{c_1, c_2, \ldots.., c_n\}, pans\{c_{31}, c_{32}\}, stirrers\{wooden\ spoon\}, in(food, pan), in(wooden\ spoon, food), stirring\ motion, stirred\}$

For a more complex template h_{15} = *Pasta bolognese*, the *bolognese sauce* can act as a composition of previously known actions over given ingredients:

$h_{14} = (stir(stir(fry(minced\ meat), chop(onion, tomatoes)), simmer(5min), season(pepper, basil, oregano), chop(mushrooms)), simmer(10min)), bolognese\ sauce$

$h_{14} = (h_1(h_1(h_5(c_1), h_2(c_2, c_3)), h_4(5), h_3(c_5, c_6, c_7), h_2(c_4)), h_4(10min)), sol_5$

4.5 Creative use of problem template

The previous template for *Pasta bolognese* can be used and re-used. Moreover, because of the posited type of knowledge encoding, the template can pop-up whenever an open search happens in the system for a general *cook* heuristic, with some of the conceptual elements ($c_1\ mincemeat, c_3\ tomatoes$) present in the fridge. The search can also be run over timing, and cooking pasta in general.

When creative solutions are proposed by the system or forced by the absence of certain ingredients, similar ingredients will be sought. Thus *mince* can be replace with *aubergine*, *onion* with *leek* or *chalotte*, *red pepper* with *yellow pepper*, *chorizo* with other types of *salami*.

When trying to change or enrich such a recipe it is reasonable to assume that "similarity" for an expert cook presupposes a set of observed, acquired and tested taste rules - like taste relations of food items that go well together $(corgettes, mushrooms)$, $(red\ pepper, tomatoes)$, or food items that give a specific taste $(chorizo, parmezan, herbs, spices)$.

Other problem templates can be used creatively in a similar fashion, employing different elements which are categorized as similar, or mixing previously held templates or structurally sound parts thereof to achieve a composed effect.

5 Mechanisms of creative search and representation construction

Mechanisms of exploration (of known concepts and problem representations structures), as well as mechanisms of construction (productive, generative, transformational operations at the level of concepts and problem representation structures) can be at play in creative problem-solving. Such mechanisms will most often act in jointly, however for the sake of analysis they will here be first described separately.

5.1 Mechanisms of creative search and matching

Generally, search for a productive problem representation can be described as taking the form of filling in a template: given c_1, c_2, c_4 and the need to fulfill sol_5, what mechanisms can you apply to reach a representation which affords the solution?

$$\{c_1, c_2, c_4, sol_5\} = PT_?$$

Various constraints and relations can be part of the problem requirements, which need accurate representation and solving.

In creative problem-solving, the subset of objects required to solve the problem might not be predefined, closed, or restricted to only the salient objects or concepts.

The search can be characterized in a variety of modes. We base the following characterisation on the direction in which the search next proceeds in the knowledge base:

- upwards - Description: Go up one level and see what problem-solving or general representational structures the concept or the structure has been involved in); check if any of their affordances is similar to the problem at hand; if found see if that structure can be a useful representation structure.

  Given: $\{c_1, c_2, sol_4\}$

  if $(\exists PT_x \supset c_1) \vee (\exists PT_x \supset c_2) | PT_x \cap sol_4 \neq \emptyset$

  Try: $\{c_1, c_2, sol_4\} = PT_x$

  This maps the current elements to a known problem representation, using its heuristics and relations to solve the initial problem.
- downwards - Description: a) Go down one level and see what concepts or properties of concepts don't work for the representation, try to replace the objects the features of which get in the way (eliminatory strategy); or b) Find which properties are essential - flag those properties for safe-keeping - (i.e. even if a form of concept blending [8] or concept generation proceeds, those properties should be inherited in the new concept).

  Given: $\{c_1, c_2, sol_4\}$

  Decompose: $c_x = c_1 \cap sol_4$

  Decompose: $c_y = c_2 \cap sol_4$

  Reassemble problem template as: $\{c_x, c_y, sol_4\}$
- sideways - Description: in memory (KB) or environment, search for similar concepts (on the various spaces) and see if they have useful properties.

  Given: $\{c_1, c_2, sol_4\}$

  if $\exists c_x$ sim $c_1 | \quad (a_x \subset c_x) \cap (sol_4 \vee \text{sim } sol_4) \neq \emptyset$

  Try: $\{c_1, c_2, c_x, sol_4\}$ or $\{c_x, c_2, sol_4\}$
- a further combination of the ones above (i.e. upwards + sideways - Description: Go up one level and check in the neighborhood of the problems that have been known to use these concepts for something that matches the required affordance here).

After each re-representation, one can check if the new problem representation has a solution whithin its inference set. Upward moves can be done automatically, triggering problem templates, relations or other structured representations in which the concepts have previously worked together. This can bring about functional fixedness as

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some salient templates are hard to avoid, and humans are not used to manipulating larger structures (like problem templates) quite as well as other smaller structures (like concepts), which are easier to contain in working memory.

Riddles, Remote Associates Tests [20] and insight problems for empirical settings all use predominantly search processes in this paradigm. Take the following riddle:

What can you catch but not throw?

The *catch* and *throw* concepts used in conjunction will initially yield sport templates, of type:

$$PT_{s1} = \{ball, catch(ball), throw(ball)\}$$

A search of semantic contextual template just over *catch*, without the motion affordances, can yield the semantic context template *catch a cold*.

With remote associates, the search proceeds in parallel. Take the test containing the words: *Falling Actor Dust*. Let's say $c_1 = falling, c_2 = Actor, c_3 = Dust$. To find their remote associate, one needs to find a word c_4 so that templates $PT_1 = \{c_1, c_4\}, PT_2 = \{c_2, c_4\}, PT_3 = \{c_3, c_4\}$ exist. When one has activated $PT_1 = Falling\ Star, PT_2 = Star\ Actor, PT_3 = Star\ Dust$, or at least two of them, and the third can be verified, one has converged upon $c_4 = Star$.

The classical candle insight problem [7] is stated as follows: *You are given a candle, a book of matches and a box of thumbtacks. Fix the lit candle unto the wall so that the wax doesn't drip below.* Various saliencies draw initial attention. The template of a candle burning effects like $\{light, wax, fire\}$. The template of fixing something unto the wall requires some material which can be $glue$ or $nail$. Wax has $glue$ properties, which probably explains why some people try to use wax to glue the candle to the wall. The participants need to focus on a representation of the kind $\{support, candle\}$, and find the support affordances of the box concept, which are not particularly salient in the $box\ of\ thumbtacks$ representation, as more likely $\{box, contains(thumbtacks), full\}$ templates are triggered.

5.2 Mechanisms of representation construction

Some of the mechanisms described above can be productive in themselves. Thus if the search is bringing two concepts together which have not been previously connected before, new relations might be observed (and it is not assumed that all such relations are previously encoded). It is commonsense that some of these relations will be interesting enough to be consolidated over time in the agent's memory.

It is not hard to imagine that some transformational processes thus happen during this search (new templates are created, new relations are seen between concepts). However we will refer here to mechanisms which are highly generative and productive by their nature (thus not accidental associations) - whether they developed out of initial search or they stood as mechanisms in their own right is a cognitive empirical questions, which this analysis cannot solve.

In this framework we will differentiate between two processes of conceptual composition (cc(i) and cc(ii)), where cc(i) is a productive form of inheriting features from two concepts in an integrative fashion, while cc(ii) aims to satisfy a higher template, or can create such a new template which is structurally different (c.f. [8]).

Thus taking the extremes of cc(i) and cc(ii), if given two concepts:

$$c_1 = \{a_1, a_2, v_1, v_2, s_1\}$$

$$c_2 = \{a_3, a_4, v_3, v_4, s_2\}$$

c_3 is a concept composed via cc(i), where:

$$c_3 = \{a_1, a_4, v_1, v_4, s_{1-2}\}$$

while c_4 is a concept composed with cc(ii):

$$c_4 = \{a_1, a2, a3, a4, v1, v2, v3, v4, s3\}$$

Thus, in their extreme form, cc(i) and cc(ii) can be simplified in this framework to:

1. maintain structure (aligned in both concepts) and import-compose features
2. maintain features (from both concepts) and import-compose structure

However, more classical examples of composition are:

$$\text{Given: } c_1 = \{a_1, a_2, v_1, v_2, s_1\}$$

$$\text{Given: } c_2 = \{a_2, a_3, v_2, v_3, s_2\}$$

$$\text{Composed: } c_3 = \{a_1, a_2, a_3, v_1, v_2, v_3, s_3\}$$

That is because generally some similar features need to exist to provide a locking point for the composition processes (and to even bring the two templates together in the first place).

This is different from processes of generalization, or observations of a relation through synthesis, which later requires naming:

$$c_1 = \{a_1, a_2, v_1, v_2, s_1\}$$

$$c_2 = \{a_2, a_3, v_2, v_3, s_2\}$$

$$c_3 = \{a_2, v_2, v_3, s_?\}$$

Thus cc(i) and cc(ii) are generative processes of a more complex nature than varying some features over the similarity neighborhood of one and the same concept (like choosing vegetarian ingredients that taste similar for an initially non-vegetarian cooking template).

Combination of problem-solving templates or RS larger than concepts is a step of even higher complexity. Many new relations can be established between concepts, and (depending on the problem domain), many more constraints are at play when searching for a RS or sub-RS that needs to fit a particular solution, affordance or relationship criteria.

Depending on the new relations, emergent affordances can be made available. Thus a problem template $PT_{15} = h_x(h_1([C]a, [C]b, [C]c), h_2([C]d, [C]e))$, where $[C]a, [C]b, [C]c$ are conceptual placeholders for a 3-slot template, will have to account for some of the relationships between whatever sets of concepts are tried on to see if application of h_1 is possible, or if new (damaging) side-effects don't appear as part of that combination.

Such productive representation construction processes can be defined as combining previously known RS's in an RS which inherits properties and/or structure from both elements. In this process, other generative, associationist and comparative processes come into play, creating new concepts, hypotheses and relations in the work necessary to come up with a new RS the properties of which can support solving of the problem.

This comparison shows that productive and generative processes are closer towards the spectrum of creative discovery and innovation, while search for a known representation that can fit the problem is more akin to empirically studied insightful problem-solving.

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6 Discussion - Searching for a representation versus constructing a representation

This analysis takes into account the degree of structure in a problem, and focuses on a framework in which the knowledge brought to the problem by the solver and the objects in the solver's environment are used as a generative set for the proposal of new solutions or hypotheses, be it via search for a productive representation or the construction of such a representation. The task of the solver is to reduce the vaguesness of insight and discovery problems by proposing representation structures (and their connected affordances and heuristics) which make the problem well-structured and adapted to the solving tools in the environment. This is done via similarity and affordance-based search, associations, combinations and transformations of previously held knowledge items and structures, interaction with external knowledge and objects available in the environment, until a representation structure is found over which classical problem-solving direct strategies can be deployed.

At their two extremes, the two mechanisms posited here can be summarized as follows:

1. Creative search: Given a knowledge base KB, use similarity encoding, associationist links and affordance sets (within the various levels of the framework) to search RSs until one is found which can fit (some of) the elements in the given problem description and affords the required solution.
2. Productive representation construction processes: Given a knowledge base KB, use RS variation, blending and composition with other RSs until you create a RS which affords the required solution.

Creative discovery problems can be accompanied by insight-related phenomenological effects, when a productive representation has been created. However empirical insight problem-solving and creative discovery are different in both process and productivity. The difference proposed here between empirical insight problem-solving and creative discovery is one of process weighting. Insight problem-solving is mostly dominated by search processes for the right representation, which might not be salient in the representation structures that are initially inferred from the objects contained in the problem. In the candle problem [7], candles being put on top of supports similar in shape to a box might have been seen by the solver. In the string problem [18], pendulums have been experienced by the solver (though perhaps not made of a string and a pair of pliers - therefore a degree of compositional creativity is involved). However, functional fixedness can get in the way of using such representations, and finding the right representation is the major impediment in such problem-solving - if the solver knows she has to make a pendulum out of one of the strings, the creative step of tying an object to the string is not as hard to come by.

In creative discovery, the accent falls on constructing a representation which is useful, despite one not existing initially in the knowledge base of the agent (sometimes not even in an analogical form). More constructive processes and transformations of known representation structures are necessary. That being said, undoubtedly many variations exist between the two ends of the creative problem-solving spectrum.

Boden [5] differentiates between combinatorial and exploratory-transformational creativity. The proposed framework contains all three types of processes: combinatorial (at relation and concept levels), exploratory (similarity based search) and transformational (at the level of RS change). Insight problem-solving and creative discovery have been defined as using all three in different degrees. For comparison reasons, this could be defined as exploratory and transformational processes dominating insight problem-solving, and combinatorial and transformational processes dominating creative discovery. However, the two process-based classifications are not entirely amenable to comparison.

The main contribution of this paper is to propose and illustrate a specific process-based differentiation in creative problem-solving. These processes are illustrated with examples of mechanisms in a partial formalization of a previously proposed theoretical framework.

Various parts of this framework can be considered similar to or amenable to implementation by already existent AI tools (which was the author's intention). Thus the sensory maps could be classified using self-organized maps [14], the pattern-recognition for shapes could be done via simple Hopfield networks [12], the conceptual anchoring in feature maps could be considered similar to conceptual spaces [9], the representation structures can be considered similar to frames [22] with fillable slots, while the choice between them related to case based reasoning [28]. The purpose of the theoretical framework was to put together knowledge representation principles which will make such a knowledge base (and the interactions with the objects in the problem-space or environment) easier to navigate and re-represent. The contribution in this sense is the pairing of knolwedge representation types and processes (which can be implemented with known tools) in order to make creative problem-solving principles more amenable to analysis.

Structural information, semantic information and functional information all play a role in this framework. The structural part involves seeing concepts as an activation of features, and problem templates as ordered collections of concepts, relations and affordances. The feature spaces themselves are considered to be structured by being organized by a metric relevant to the specific feature space. However this organization turns them into semantic spaces for the concepts anchored in these features.

Thus concepts are semantically expressed via the features they are anchored into. Furthermore, a concept can be considered related on a specific dimension to a concept with which it shares features on that dimension. Concepts also gain semantics via the context of the problem templates (or other representation structures and relations) they are involved in, with various features of a particular concept being emphasized by becoming productive in a particular context.[7]

Functional information can be encoded and decoded in such a framework both explicitly and implicitly. Examples of explicit functional information are the affordances connected to or part of various concepts, problem templates and other RS's (i.e. relations, complex concepts, etc). Implicit functional information is present via the participation of various concepts and relations in various problem templates, thus is encoded within the structure of such representation. In this sense, a concept affords the solving with a particular template, and a template affords the use of particular concepts (or others with similar structure), in a way similar to objects affording particular actions.

7 Conclusions and further work

This paper has approached creative problem-solving from the perspective of the relation between the structure in such problems (which can be missing, unclear, non-salient, not leading to productive inferences, etc.) and the demands this makes upon representation

[7] Similarly, the semantics of a feature are expressed by its place in a feature map, and the various concepts/contexts in which it is triggered.

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structure. The paper has proposed a process-based differentiation of creative problem-solving classes, using the processes involved in rallying the productive representation structure. The two types of processes considered for such a differentiation here have been *search* versus *constructive* processes. They have been exemplified in the context of a previously described framework [26], which has been (partially) formalized for these purposes. The two classes described here involve a higher amount of creative search (Riddles, Remote Associate problems, empirical insight problems) or a higher amount of representation construction processes (e.g. concept and RS generation through composition and blending, creative discovery problems).

The process differentiations posited here needs studying in cognitive empirical settings. This comparison proposes the testable assumption that human solvers good at one type of problems of creative search for representation (like Riddles) will be good at others too (like Remote Associates or empirical insight problems), when one controls for the different types of sensory encoding.

This paper has proposed that certain problems normally used for the assessment of creativity (such as Riddles, Remote Associate problems, insight problems used in empirical settings) belong to a class which requires processes of creative search more than processes of construction. The different kinds of problems belonging to the creative construction of a productive representation class need further dissemination; such different types also need to be related to tests administered in empirical settings.

The difference in difficulty for human problem-solvers between the various levels of such problems need to be assessed. Computational difficulty in this framework can be assessed as the number of manipulations of structure required, or the distance of search necessary to reach a productive representation structure. Controlled computational experimentation could further help the design of such classes of problems of different levels of difficulty.

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